Information Fusion for Colorectal Polyps Medical Image Segmentation

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RESEARCH

Information Fusion for Colorectal Polyps Medical Image Segmentation

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Abstract

Training a deep neural network often requires a huge amount of annotated data, which is scarce in the medical image analysis domain. In this work, we present a simple yet effective strategy that relies on the information fusion to enhance existing neural networks. The proposed approach utilizes information from different spatial scales and combines them in a learnable way. Experimental results on two benchmark datasets demonstrate that the proposed fusion module improves the segmentation performance of state-of-the-art neural networks.

Keywords: Medical image analysis; Polyps segmentation; Neural network; Semantic segmentation; Information fusion

Background

Semantic segmentation is a common computer vision task in which each pixel in an image is assigned to a pre-defined category [1]. It has been widely used in applications such as landscape mapping, autonomous driving, and medical image analysis [2, 3]. In the last decade, training a deep convolutional neural network (CNN) to segment the image has replaced the hand-crafted features to become a common practice due to its superior performance. It is well understood that deep neural networks are notoriously data hungry in-

sofar as effectively training the model is concerned. As opposed to the application of semantic segmentation in the industry, deploying a segmentation system for medical image analysis has been found challenging. Lack of annotated data has always been a major obstacle in the medical image analysis community [4]. This is attribute to the manner on how medical images are labeled. Unlike natural images that can be easily obtained, medical images are hard to acquire due to the data privacy concern. To make matters worse the annotator is required to have domain expertise for labeling medical images.

Colorectal cancer is the third most commonly diagnosed cancer and the fourth cause of cancer death around the world [5]. As a precursor to the colorectal cancer, polyps are abnormal tissue growths on the inner lining of the colon or rectum. In clinical practice, colonoscopy is the preferred technique for detection and assessment of polyps. Therefore, developing

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a method to accurately segment polyps in colonoscopy images is of great interest as it helps the doctor to identify polyps at an early stage. However, segmenting polyps is a challenging task as the same type of polyps appears in a high variety of color, size and texture. Despite the advancement in colonoscopy, the boundary between polyps and surrounding mucous membrane is usually not very sharp as shown in the Figure 1.

To address these challenges, in this paper, we propose a novel information fusion module to improve the performance of existing segmentation networks. The key idea is to combine features from different layers in a data adaptive way. We evaluate the proposed method on two publicly available datasets, Kvasir-SEG [6] and CVC-612 [7], for polyp segmentation in colonoscopy images. The results demonstrate that the proposed fusion module improves on multiple network architectures for medical image segmentation.

The remainder of this paper is organized as follows. We introduce the related work in Section and describe the proposed approach in Section . Section describes the two datasets along with the segmentation results. Concluding remarks are provided in Section 0.1.

Related work

To address the label scarcity problem, plenty of machine learning techniques have proposed in the last few years. Existing techniques can be roughly grouped into two broad categories: efficient training and data feature enhancement. To improve the network training efficiency, a technique like active learning aims to train the network with as less as possible labeled data by selecting the most informative samples [8]. Transfer learning allows a model to be fine-tuned with a much smaller amount of data by pre-training the network on a large-scale dataset like ImageNet [9], where labels are relatively easy to obtain [10]. Semi-supervised learning takes a different route by extracting the informative features from unlabeled data [11].

Data feature enhancement, on the other hand, focuses on creating more discriminative features and exploiting the relationship between data samples. Synthetic data generated with generative adversarial network (GAN) [12] has proven to be very effective for improving the model performance [13, 14]. Statistical shape and appearance models have also been used to generate training samples with higher data variance that helps improve the robustness of the model [15]. The hierarchical features in CNN provide a natural way to address the object scale variance issue in medical image segmentation. U-Net [16] and its variants [17–20] capture the multi-scale information by connecting features from shallow and deep layers. Attention-based methods [21–24] guide the training to focus on important image regions such as object edges such that the segmentation accuracy can be improved.

Method

In this section, we introduce the proposed information fusion module. We begin by describing the base network, fully convolution network (FCN) [1], and the feature refinement unit [25]. We then explain how the multi-scale features are combined through the information fusion module. Figure 2 depicts our network architecture.

Fully convolutional network (FCN) has been extensively used for semantic segmentation since it was introduced in 2015 [1]. To simplify the flowchart, we omit the convolutional layers and the output (softmax) layer in FCN in Figure 2. The convolutional features after four pooling layers, which are commonly known as FCN-32s, FCN-16s, FCN-8s, and FCN-4s, are sent through the information fusion module before making the prediction.

The information fusion module not only improves the discrimination ability of features, but also aggregates features at different level in a learnable fashion. In particular, the convolution features at each stage

¹are first connected to a feature refinement unit (FRU).

²The detailed architecture of a FRU is shown in Fig-
³ure 2. Inspired by the RefineNet [25], we add two ad-
⁴ditional convolutional layers and associated ReLU ac-
⁵tivation layers [26] in combine with a residual connec-
⁶tion. This refinement process has shown to be effec-
⁷tive in dealing with fine-scale features [25]. When used
⁸in colonoscopy image segmentation, the feature refine-
⁹ment is helpful for segmenting polyps that are rela-
¹⁰tively small as compared to the image size.

¹¹

¹² It is well known that early layers in a CNN are re-
¹³sponsible for extracting shallow, fine, and appearance
¹⁴information from the data, while layers in later stages
¹⁵tend to produce features at a coarse scale and are re-
¹⁶lated to the semantic information [27, 28]. The suc-
¹⁷cess of U-Net [16] has shown that combining these
¹⁸two types of features is critical for producing accurate
¹⁹segmentation map for medical images. Instead of di-
²⁰rectly concatenating all features, the outputs of FRU
²¹are added together and followed by a 1×1 convolu-
²²tion. This essentially learns a weight for features from
²³each layer. Compared to a feature concatenation or a
²⁴feature summation, weights for each component can
²⁵be learned through the error back propagation. There-
²⁶fore, features that contain different information can be
²⁷combined in a data-driven way. It is worth noting that
²⁸we choose FCN as the base network for illustration
²⁹purpose. The proposed information fusion module is
³⁰flexible and generic. We can attach different number
³¹of FRUs based on the feature groups. For example,
³²when the proposed information fusion module is used
³³with U-Net, we can attach one FRU after each skip
³⁴connection, which results in a 4-stage fusion. The in-
³⁵formation fusion module can also be used with other
³⁶network architectures as long as the convolutional fea-
³⁷tures can be extracted from different depths. The stan-
³⁸dard pixel-wise cross entropy loss is used to train the
³⁹network.

Experiments

¹

In this section, we evaluate the proposed method by²
 applying them to two publicly available polyp segmen-³
 tation datasets. We compare the performance of multi-⁴
 ple networks with and without adding the information⁵
 fusion module.⁶

⁷

0.1 Datasets and Baselines

⁸

Kvasir-SEG [6] is a recently released dataset for polyp⁹
 segmentation. It consists of 1000 images and their cor-¹⁰
 responding ground truth. These images were manually¹¹
 labeled by a medical doctor and reviewed by an expe-¹²
 rienced gastroenterologist from Vestre Viken Health¹³
 Trust in Norway. CVC-612 [7] is a benchmark dataset¹⁴
 that has been used in many polyps segmentation stud-¹⁵
 ies. It contains 612 images that were extracted from¹⁶
 31 colonoscopy videos. For both datasets, each pixel¹⁷
 in the image is labeled as either polyp or non-polyp.¹⁸

To evaluate the efficacy of the proposed method,¹⁹
 we compare the performance before and after adding²⁰
 the information fusion module with multiple networks,²¹
 including FCN [1], U-Net [16], U-Net++ [17], Re-²²
 sUNet++ [19], PraNet [29].²³

²⁴

Results

²⁵

For both datasets, we follow the common experimen-²⁶
 tal setup used in [19, 29] by randomly split the data²⁷
 into three sets, training (80%), validation (10%), and²⁸
 testing (10%). The performance of network is mea-²⁹
 sured with standard semantic segmentation metrics,³⁰
 Dice and mean Intersection over Union (mIoU).³¹

All networks are implemented using PyTorch frame-³²
 work [30]. The experiments are conducted on an AWS³³
 EC2 p3.2xlarge instance. For baseline networks, i.e.,³⁴
 without information fusion module, we use numbers³⁵
 reported by the original authors. To have a fair com-³⁶
 parison, we use the same hyperparameters as the au-³⁷
 thors specified in the original papers when training the³⁸
 network with information fusion module. For networks³⁹

that the training details are not provided, we train the network 100 epochs with a batch size 16. The initial learning rate is set to 0.01. For optimization, we use the SGD optimizer with a cosine decay for learning rate schedule [31]. We also use the standard data augmentation, such as random flip, crop, rotation, and color jittering, etc., to improve the model performance.

Table 1 shows the segmentation results of all networks. As can be seen that the information fusion module (indicated by (IF) in the table) consistently improved the model performance on both datasets. When applied to a basic network like FCN [1], the information fusion module improved Dice from 0.794 to 0.822 by 3.5%, and mIoU from 0.763 to 0.792 by 3.8% on the Kvasir-SEG dataset. A similar trend can be observed on the CVC-612 dataset as well as for U-Net. With advanced variants of U-Net, the additional connections in U-Net++ [17] and ResUNet++ [19] are expected to enhance the feature combination from different layers. The model with information fusion module still achieved higher Dice and mIoU. We attribute this to the weighted summation with learned weights compared to simple feature concatenation and feature summation. The improvement on the recently published PraNet [29] is relatively small as opposed to other networks. This is because the PraNet also adopts multi-scale feature fusion using an attention module, which shares the same motivation as the proposed information fusion module. It is worth mentioning that the performance achieved by the PraNet is the state-of-the-art on both datasets. Considering that the PraNet results are close to the empirical upper bound of these two datasets, the improvement achieved by the information fusion module is considerably significant.

Fig. 3 shows the qualitative results for models with and without the information fusion module on CVC-612 and Kvasir-SEG datasets. We observe similar trends from all the compared networks and choose

FCN and PraNet as examples. As can be seen that networks with the proposed information fusion module produced segmentation masks with sharper edges compared to the ones produced by networks without the proposed module. The basic network (FCN and PraNet) tended to make mistake when the boundary between polyps and surrounding mucous membrane is blurry. With the information fusion module, the networks (FCN(IF) and PraNet(IF)) were able to separate these polyps from background. We attribute this improvement to the ability to combine fine-scale features with coarse-scale features.

Conclusion

In this paper, we have proposed a novel approach to improve semantic segmentation networks for medical image segmentation. The proposed information fusion can be easily incorporated as a module for all common segmentation networks. The feature refinement and weighted feature summation that provided by the information fusion module have been demonstrated to be effective in improving the segmentation performance on real polyp segmentation datasets when compared with other basic networks.

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Abbreviations

CNN: Convolutional neural network; GAN: Generative adversarial network; FCN: Fully convolutional network; FRU: Feature refinement unit; mIoU: mean intersection-over-union; AWS: Amazon web service; SGD: Stochastic gradient descent.

Availability of data and materials

The CVC-612 dataset analysed during the current study are available at <https://polyp.grand-challenge.org/CVCClinicDB/>. The Kvasir-SEG dataset analysed during the current study are available at <https://datasets.simula.no/kvasir-seg/>.

¹ **Ethics approval and consent to participate**

²Not applicable.

³ **Competing interests**

⁴The authors declare that they have no competing interests.

⁵ **Consent for publication**

⁶Not applicable.

⁷ **Authors' contributions**

⁸ZZ and YD equally contributed to this work. ZZ designed and implemented the algorithm and was the major contributor in writing the manuscript. YD, ⁹WH, and FP helped with the experiments and results analysis. BL and JH ¹⁰provided research guidance, reviewed and revised the manuscript.

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Figure 1 Example colonoscopy images of polyps (top row) and associated labels (bottom row) from Kvasir-SEG [6] dataset.

Figure 2 Network architecture of a standard FCN with the proposed information fusion module.

Figure 3 Segmentation results of different methods on CVC-612 (top row) and Kvasir-SEG (bottom row) datasets.

Table 1 Segmentation results of networks with (indicated by (IF)) and without the information fusion module on Kvasir-SEG and CVC-612 dataset.

Method	Kvasir-SEG		CVC-612	
	Dice	mIoU	Dice	mIoU
FCN [1]	0.794	0.763	0.768	0.728
FCN (IF)	0.822	0.792	0.791	0.762
U-Net [16]	0.818	0.746	0.823	0.755
U-Net (IF)	0.833	0.770	0.845	0.773
U-Net++ [17]	0.821	0.743	0.794	0.729
U-Net++ (IF)	0.831	0.767	0.819	0.742
ResUNet++ [19]	0.813	0.793	0.796	0.796
ResUNet++ (IF)	0.827	0.812	0.815	0.816
PraNet [29]	0.898	0.840	0.899	0.849
PraNet (IF)	0.899	0.849	0.903	0.857

Figures

Figure 1

Example colonoscopy images of polyps (top row) and associated labels (bottom row) from Kvasir-SEG [6] dataset.

Figure 2

Network architecture of a standard FCN with the proposed information fusion module.

Figure 3

Segmentation results of different methods on CVC-612 (top row) and Kvasir-SEG (bottom row) datasets.